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Effects of parameter and data uncertainty on long-term projections in a model of the global forest sector

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ABSTRACT

This study explored the consequences for long-term projections and impact analysis of the uncertainty in model parameters and initial conditions. Using the Global Forest Products Model, multiple replications of projections were carried out with parameters or initial condition data sampled randomly from their assumed distribution. The results showed that parameter uncertainty led to uncertainty of the projections increasing steadily with the time horizon, and more rapidly than the uncertainty stemming from initial conditions. Among the parameter uncertainties, those in the supply and demand elasticities tended to dominate the uncertainty in the other parameters describing forest growth, manufacturing activities, and trade inertia. In an application to impact analysis it was found that, due only to the uncertainty of the model parameters, and conditional on other assumptions, an assumed rise in global temperature of 2.8 °C over a century caused the forest stock in 2065 to be 2.4% to 4.0% higher in developed countries, and 2.5% to 3.9% lower in developing countries, with 68% probability, a conservative estimate of the true uncertainty given all the other factors involved in such a prediction.

1. Introduction

"How sensitive are your results to the assumptions regarding the values of the parameters?" This question, frequently and legitimately asked by reviewers of forecasting and policy papers based on forest sector models, is rarely answered in full. At best, one or two parameters subjectively deemed important for the analysis may be changed to trace their effects on the results. More extensive sensitivity analyses are rare (see Chudy et al., 2016 for a review). One notable exception for forest sector models is in Kallio (2010) who applies Monte Carlo simulation to a model for Finland to determine how the uncertainties of the parameters and world forest product prices affect projections. She finds that while the uncertainty in the parameters has a moderate impact, the unpredictability of world product prices (that are also affected by exchange rates) leads to much variation in projections. Skog (2008) also used Monte Carlo simulation to assess the uncertainty of estimates of carbon stored in harvested wood products in the United States in 2005, concluding that the uncertainty is between −23% and +19%. Heath and Smith (2000) find that uncertainty in carbon inventory in the private forests in the United States is approximately ± 9% in the year 2000, rising to 11% in projection year 2040.

A large degree of the uncertainty lies in the underlying economic data from which forest sector models are built. While it is well known that global databases like those provided by the International Monetary Fund (IMF), the Organization for Economic Cooperation and Development (OECD), the World Bank, and the Food and Agriculture Organization (FAO) of the United Nations have serious measurement errors (Van Bergeijk, 1995; Jerven, 2014), forest sector models must still rely on them for development indicators such as gross domestic product (GDP) and population, as well as for data on forest resources. Yet, any error in historical data will be retained in parameter estimates and in the initial conditions of the model, and carried forward in projections and scenario analysis.

Beyond uncertainty in the initial conditions of the forest sector and its context, there is uncertainty due to the way in which the model parameters are estimated. Quantitative models rely on parameters obtained econometrically or by other methods, such as price and income elasticities of demand, and parameters in equations of forest area change and supply shifts. Inevitably, errors in the historic data and in theoretical formulations will lead to faulty interpretations of the past (Morgenstern, 1963; Boumans, 2012), and one is left to construct proxies for the unknown relationships governing the phenomena under study (Griliches, 1986). Consequently, these uncertainties can lead to considerable variation in model projections and policy analysis (Kann and Weyant, 2000; Orrell et al., 2001). Recognizing that measurement errors are an unavoidable characteristic of historical data and that

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inaccuracy is inherent in all model parameters has led researchers to build this uncertainty explicitly into the model structure with Monte-Carlo simulation methods by sampling randomly from the distributions of the data or parameters (O'Neill et al., 1980; Abler et al., 1999).

The present study followed Kallio's (2010) suggestion to investigate the effect of parameter and data uncertainty in the case of widely applied global forest sector models. Using as a case study the Global Forest Products Model (GFPM, Buongiorno and Zhu, 2017) this paper concentrated on the issues of uncertainty in parameter values and initial conditions and their consequences for projections and impact analysis. With the goal of guiding future research, the work gave special attention to the uncertainty in different parameter types: demand and supply elasticities, forest growth parameters, manufacturing costs and input-output coefficients, and trade inertia parameters. The method consisted in making multiple replications of projections to 2065 with all parameters, or only parameters of a specific type sampled randomly from their assumed distributions.

In the GFPM the calculation of the equilibrium in each projected period is a constrained quadratic optimization, and non-linear recursive equations link one period solution to the next. The projections obtained with such a highly nonlinear system may be sensitive to the initial conditions, so that a small change in the initial state (the base year data of the GFPM) could lead to large variations in the predictions. This sensitivity of the GFPM to initial conditions was tested with replications of projections to 2065 with initial conditions randomly selected from their assumed distribution.

The last part of the paper reports on the consequences of model parameter uncertainty for impact and policy analysis. Here, impact analysis referred to the effect of an environmental or policy change on a projection, other things equal. As an example we used the potential effect of a rise in global temperature on the forest sector. In this context the main concern was not the future level of a particular variable such as the forest stock of a country, but the difference in future forest stock with or without the temperature increase. How this difference varied due to uncertain model parameters was the object of study.

2. Methods and data

The GFPM calculates every year a global market equilibrium across countries and products, linked to past equilibria. The current model deals with 180 countries, forest area and stock, and 14 wood product groups ranging from fuelwood to paper and paperboard. More details concerning the formulation and the computer implementation are available in Buongiorno and Zhu (2017).[1]

The spatial global economic equilibrium of the forest sector in a given year is obtained by quadratic programming. The objective function is the social surplus in the sector, which is maximized by competitive markets (Samuelson, 1952; Takayama and Judge, 1971). This surplus is equal to the value of the products to consumers (area under all the inverse demand curves), minus the cost of supplying the raw materials (area under their inverse supply curves), minus the transformation cost at each stage of manufacturing, and minus the transport cost between countries. The constraints express the equilibrium conditions: for each country and product, the quantity imported plus the domestic supply and the manufactured quantity must equal the domestic demand plus the quantity used in manufacturing other products, plus exports.

In view of the objective of this study, concerning the impact of parameter and data uncertainty on projections, twenty replicated runs of the current GFPM (Buongiorno and Zhu, 2017) were carried out from the base year 2014 up to 2065. In each run, all or specific parameters were drawn randomly from their assumed distribution. The coefficients of variation of the 2065 projections were used to assess the variability of the projections and to compare them with the projection obtained with the model with average parameters.

Specifically, twenty replications were carried out with random selections of each of the following parameter categories, other parameters being held constant at their average value:

(i) demand elasticities,
(ii) supply elasticities,
(iii) forest parameters,
(iv) manufacturing parameters,
(v) trade inertia parameters.
(vi) all of the above.

In addition, twenty replications were carried out to determine the effect of uncertainty in the initial conditions, i.e. the production, consumption, trade, and price data in the base year, with the model parameters held at their average value. Last, twenty replications were done to assess the consequences of uncertainty in all the GFPM parameters when the model was applied for impact analysis such as the long-term effect of climate change on the forest sector.

2.1. Effect of uncertainty in demand elasticities

In each year and country, the demand of each end product (fuelwood, sawnwood, panels, paper and paperboard) shifts over time according to GDP growth and the attendant GDP elasticity, α_y. The current demand curve is defined by the consumption at last year's price after the demand shift, and by the price elasticity, δ. The values of the demand parameters and their standard errors are in Table 1. To judge the impact of this source of uncertainty on the projections, other things being equal, the GFPM was run twenty times, each time with a different set of randomly drawn elasticities, holding all other parameters at their average value. For example, the price elasticity of demand for a product in a country was obtained from:

$$\delta = F^{-1}(r \mid \bar{\delta}, s_\delta) \quad (1)$$

Where F^{-1} was the inverse of the normal cumulative density function, r was a uniformly distributed random number in the [0,1] interval, $\bar{\delta}$ was the mean elasticity and s_δ was its standard error (Table 1). The GDP elasticities were randomized in similar fashion.

2.2. Effect of uncertainty in supply elasticities

The wood supply (fuelwood and industrial roundwood) in a country and year is defined by the current production at last year's price, and the price elasticity of supply, λ. The supply shifts with changes in forest stock, according to elasticities, β_I. For other fiber and waste paper the supply depends on price and GDP. The supply elasticities and their standard errors are in Table 2.

To assess the partial effect of the uncertain supply elasticities on projections twenty replications were carried out, each with a new set of elasticities obtained with the analog of Eq. (1) and the expected values and standard errors of the elasticities in Table 2.

2.3. Effect of uncertainty in forest parameters

The rate of change of forest area, g_a in a country and year is defined by the following equation, based on the "environmental Kuznets" theory (Buongiorno, 2014):

$$g_a = (\alpha_0 + \alpha_1 y')e^{\alpha_2 y'} \quad (2)$$

Where y' is the income per capita in a country and year. With $\alpha_1 > 0$, and $\alpha_2 < 0$ Eq. (1) yields negative growth rates at low

[1] The software, documentation, and data for the GFPM version 2017 are available free of charge for academic research at: http://labs.russell.wisc.edu/buongiorno/welcome/gfpm/

Table 1
Mean and standard error (SE) of elasticities of end products demand in the GFPM.

	Elasticity			
Commodity	Price (δ)	SE	GDP (α_y)	SE
Sawnwood[a]	−0.17	0.05	0.24	0.10
Veneer & plywood[a]	−0.37	0.04	0.62	0.08
Particleboard[a]	−0.51	0.05	0.59	0.09
Fiberboard[a]	−0.58	0.05	0.93	0.15
Newsprint[a]	−0.22	0.04	0.43	0.06
Printing & writing[a]	−0.65	0.05	0.44	0.06
Other paper[a]	−0.38	0.05	0.29	0.06
Fuelwood[b]	−0.12	0.06	−0.14	0.13
Other industrial roundwood[b]	−0.12	0.06	−0.03	0.06

[a] Buongiorno (2015)
[b] Authors' estimates.

Table 2
Mean and standard error (SE) of elasticities of raw materials supply in the GFPM.

	price (λ)		GDP		Stock (β_I)	
Product	Mean	SE	Mean	SE	Mean	SE
Fuelwood[a]	1.31	0.50			1.10	0.20
Industrial roundwood[a]	1.31	0.50			1.10	0.20
Other industrial roundwood[a]	1.31	0.50			1.10	0.20
Other fiber	1.00[b]	0.50[b]	0.14[c]	0.12[c]		
Waste paper	1.00 [b]	0.50 [b]	0.67 [c]	0.05 [c]		

[a] Turner and Buongiorno (2006)
[b] Authors' assumptions.
[c] Conditional on price elasticities.

income, which increase and become positive at higher income, and decrease progressively to zero at the highest income levels. For each country, α_0 is such that in the base year the observed growth rate, g_a^0 is equal to that predicted by Eq. (2), given the income per capita y'.

The national forest stock evolves over time according to the growth rate of the forest stock left after harvest, g_u. This growth rate is inversely related to the forest density (residual stock level, I, per unit area, A), according to the equation:

$$g_u = \gamma_0 \left(\frac{I}{A}\right)^{\sigma} \quad (3)$$

Where σ is a constant elasticity and γ_0 is such that in the base year the observed growth rate, g_u^0, in each country is equal to the growth rate predicted by Eq. (3) given the stock per unit area.

The national drain from the forest depends on the harvest of industrial roundwood and fuelwood, taking into account that only a fraction of the harvested fuelwood, θ, comes from the forest, and that the drain from the forest exceeds the harvest by a fraction, μ, reflecting various losses. The parameters θ and μ vary by country.

For each of twenty replicated runs of the GFPM a set of random values of the parameters α_1, α_2, and σ were obtained for each country with the analog of Eq. (1) using the mean and standard errors of the parameters in Table 3.

The same Eq. (1) was applied to obtain for each country random values of the initial growth rates of forest area and stock, g_a^0, g_u^0, the fraction of fuelwood that came from the forest, θ, and the ratio of inventory drain to harvest volume, μ. Considering the unknown, but potentially large errors in these parameters, their coefficient of variation (CV) was set at 25% of their estimated value in the base year. For example, the standard error of the initial growth rate of forest stock was 0.25 g_a^0 where g_a^0 was the estimated growth rate in the version of the model with average parameter values.

Table 3
Mean and standard error (SE) of forest parameters in the GFPM.

Linear area growth Kuznet's curve parameter, α_1	
Mean	0.0014
SE	0.0007
Exponential area growth Kuznet's curve parameter, α_2	
Mean	−0.09
SE	0.04
Elasticity of stock growth rate with stock density, σ	
Mean	−0.41
SE	0.13

Source: Buongiorno (2015)

2.4. Effect of uncertainty in manufacturing parameters

The manufacturing activities (e.g. production of sawnwood from industrial roundwood or of paper from pulp) are expressed in the GFPM by input-output coefficients, a_{ikn}, the input of product k per unit of manufactured product n in country i. With this transformation comes a manufacturing cost, the marginal cost of the inputs (labor, energy, capital, other materials), beyond the cost of wood and fiber endogenous in the model. The mean and standard error across countries of the input-output and manufacturing cost parameters are in Table 4. In the GFPM these parameters vary by country, and they are calibrated so that the base-year solution closely replicates the observe data (Buongiorno and Zhu, 2015).

In each replication run, the analog of Eq. (1) was applied to each country to obtain a random set of input-output coefficients and manufacturing costs, based on their average value in the GFPM and the standard errors in Table 4.

In addition, the GFPM assumes almost constant returns to scale, expressed by a low elasticity of the manufacturing cost with respect to output $s = 0.1$. For each of twenty replicated runs, random values of s were obtained across countries and industries with Eq. (1), the same mean value of 0.1 and a coefficient of variation of 25%.

2.5. Effect of uncertainty in trade inertia parameters

The GFPM uses “trade Inertia” parameters whereby the current trade must stay within a lower bound, T^L, and upper bound, T^U, relative to the previous period. The trade inertia parameters vary by country, and their means and standard errors are in Table 5. In the standard simulations of the model, the trade inertia parameters are equal to the mean value. In the replications performed here, random values of the trade inertia parameters for each country were determined with the analog of Eq. (1) based on the means and standard errors in Table 5.

2.6. Effect of uncertainty in initial conditions

To test the sensitivity of the projections to the accuracy of the base-year data the GFPM was run twenty times up to the year 2065, each time with random initial conditions. Specifically, the base-year data on production, consumption, import, export, price, transport cost, and GDP per capita were drawn randomly in each replication from a normal inverse distribution analog to Eq. (1), with a mean equal to the reported FAOSTAT and World Bank WDI data, and assuming a coefficient of variation of 5%.

2.7. Effect of parameters uncertainty on impact analysis

The method used twenty pairs of replications, each pair selecting a random set of parameters (demand and supply elasticities, forest, manufacturing, and trade inertia parameters) from their assumed distributions. With each parameter set two projections to 2065 were done

Table 4
Mean and standard error (SE) of input-output coefficients and manufacturing costs in the GFPM.

Input		Output								
		Sawnwood	Veneer & plywood	Particleboard	Fiberboard	Mech. Pulp	Chem.& Sem. Chem. Pulp	Newsprint	Printing & writing paper	Other paper & paperboard
Industrial roundwood	Mean	1.82	1.92	1.11	1.16	2.74	3.57			
(m^3/m^3 or m^3/t)	SE	0.05	0.06	0.02	0.02	0.12	0.04			
Mechanical pulp	Mean							0.20	0.09	0.08
(t/t)	SE							0.02	0.02	0.02
Chemical pulp	Mean							0.32	0.24	0.34
(t/t)	SE							0.05	0.04	0.03
Other fiber pulp	Mean							0.01	0.06	0.08
(t/t)	SE							0.01	0.02	0.02
Waste paper	Mean							0.53	0.58	0.47
(t/t)	SE							0.05	0.08	0.03
Manufacturing cost	Mean	89.9	388.6	178.2	333.6	190.4	226.0	219.5	623.3	616.8
($/$m^3$ or $/t)	SE	5.6	7.6	3.0	3.9	16.6	9.2	19.2	27.3	21.3

Source: Buongiorno and Zhu (2015), with updated data.

Table 5
Mean and standard error (SE) of trade inertia parameters in the GFPM (%).

	Mean	SE	Mean	SE
Fuelwood	6.1	0.6	5.9	0.6
Industrial roundwood	5.2	0.4	3.3	0.4
Sawnwood	3.9	0.3	5.8	0.3
Veneer & plywood	3.0	0.3	5.9	0.2
Particleboard	5.7	0.4	8.5	0.3
Fiberboard	7.2	0.4	12.9	0.3
Mechanical pulp	−0.8	0.7	−0.7	0.5
Chemical pulp	3.5	0.5	4.5	0.2
Other fiber pulp	4.6	0.6	2.9	0.4
Waste paper	12.8	0.3	3.5	0.3
Newsprint	2.1	0.4	4.6	0.2
Printing & writing paper	5.5	0.3	8.3	0.2
Other paper and paperboard	6.2	0.3	6.5	0.2

Source: Authors' estimates.

with the GFPM, one with temperature change and the other without it to obtain by difference the impact of the temperature change and thus observe how this difference varied with the model parameters, all other assumptions being the same.

The global scenario used in the projections from 2013 to 2065 was the IPPC scenario A1B (Nakicenovic et al., 2000), extended and modified for the purpose of the United States Forest Service 2010 RPA Assessment (USDA Forest Service, 2012). For the GFPM simulations, the three main exogenous variables from this scenario were the growth of GDP and population, and the rise in temperature, estimated at 2.8 °C over one century (IPCC, 2007).

Way and Oren (2010) find that trees in boreal, temperate, and tropical zones respond differently to increased temperature. The response is positive and largest in boreal ecosystems, much lower but still positive in temperate ones, and negative in tropical zones. The response is estimated by equations that summarize the results of numerous experiments with tree growth (Way and Oren, 2010).

The equations implied that a rise in temperature of 2.8 °C over a century as in the A1B scenario increased the growth rate of trees by 0.14% per year in boreal regions. In contrast, in tropical forests the same rise in temperature decreased the forest growth rate by 0.09% per year, and in temperate forests the annual growth rate increased by a modest 0.02%. Here, countries were broadly classified as having mostly forests of the boreal, temperate, or tropical type according to their mean monthly annual temperatures (MAT) from 1961 to 1999 (World Bank, 2011). For the purpose of this study, among the 180 GFPM countries, those with MAT ≤ 1.5 °C were classified as boreal, those with 3 °C ≤ MAT ≤ 19.7 °C as temperate and those with MAT ≥ 20 °C as tropical.

Table 6
Effect of uncertainty in all parameters combined. Coefficient of variation (%) of industrial roundwood production, consumption, import, export, and price in 2065 for twenty replications with all parameters drawn randomly from their assumed distributions.

	Production	Consumption	Import	Export	Price
AFRICA	25	17	8	60	
Egypt	106	42	24	25	33
Nigeria	244	244	64	179	44
South Africa	52	34	20	81	36
N/C AMERICA	23	22	22	62	
Canada	72	68	28	199	29
Mexico	33	32	106	33	23
United States	25	19	17	67	13
SOUTH AMERICA	15	13	144	101	
Argentina	17	17	36	125	22
Brazil	18	17	19	114	19
Chile	44	40	46	178	18
ASIA	19	10	13	81	
China	35	15	17	21	31
India	58	45	116	104	49
Indonesia	23	22	101	176	23
Japan	46	33	92	394	28
Korea, Rep.	43	35	107	176	35
Malaysia	41	37	158	181	34
OCEANIA	26	19	76	59	
Australia	15	27	25	40	21
New Zealand	32	28	26	128	21
EUROPE	13	14	33	23	
EU-28	19	17	33	51	
Austria	38	37	64	27	16
Finland	46	30	86	78	20
France	64	49	19	110	35
Germany	48	36	97	56	19
Italy	47	33	59	49	21
Russian Fed.	22	18	18	38	20
Spain	45	38	72	144	23
Sweden	35	33	162	38	22
United Kingdom	38	37	127	263	99
DEVELOPED	11	12	35	15	
DEVELOPING	14	8	14	53	
WORLD	6	6	10	10	21

3. Results

3.1. Effects of combined uncertainty in all parameters

Table 6 shows the relative variation in projections, expressed by the coefficient of variation in 2065, resulting from uncertainty in all the parameters combined, for industrial roundwood production, consumption, trade, and prices in world regions and major countries. The

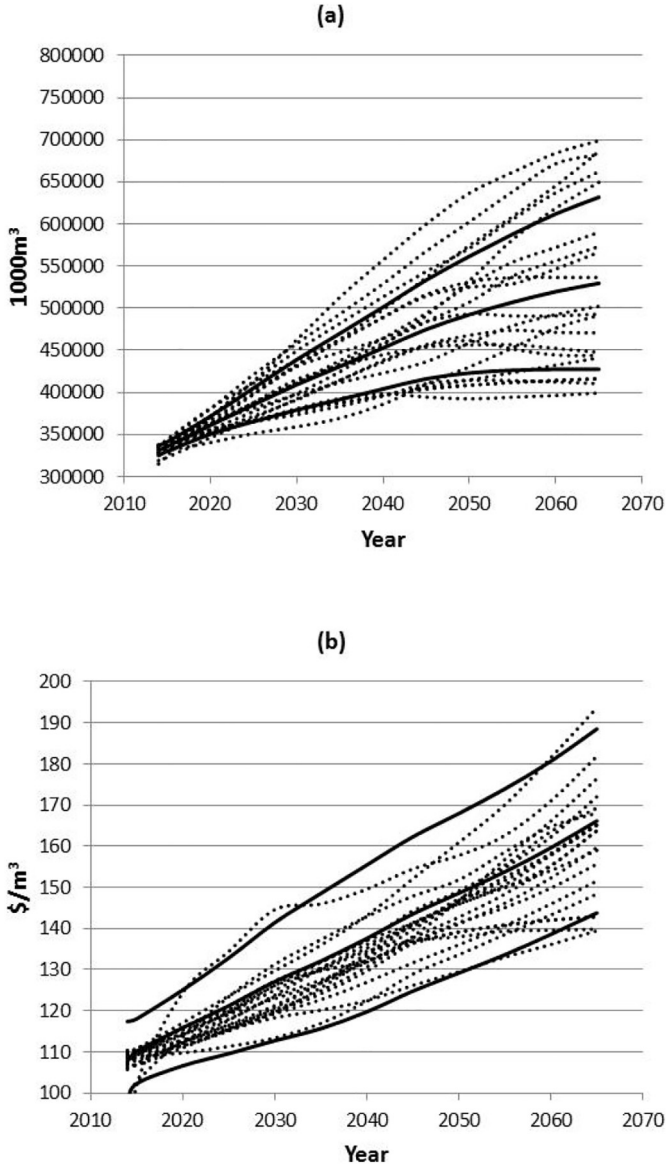

Fig. 1. GFPM projections of industrial roundwood consumption (a), and price (b) in the United States from 2014 to 2065. Dotted lines are twenty replications with parameters drawn randomly from their assumed distribution. Solid lines are the average projection and the average plus or minus one standard deviation.

CVs were based on twenty replications of GFPM projections with randomly drawn parameters of all types: demand, supply, forest, manufacturing, and trade inertia.

At world level, the coefficient of variation of the projections in 2065 was largest for the price of industrial roundwood (21%), followed by the CV of imports and exports (10%) and by that on production and consumption (6%). The larger CV for trade and price projections tended to persist at regional and country level. However, the uncertainty was much larger for regions than for the world total. For example, the CV of industrial roundwood production was 13% for Europe, 19% for Asia and 23% for North and Central America. For individual countries, the CV reached 58% for India and 244% for Nigeria.

An example of the widening of uncertainty over the projected period is in Fig. 1. The Figure shows twenty replications of projections of industrial roundwood consumption and price in the United States from 2014 to 2065 obtained with parameters drawn randomly from their assumed distribution, as well as the average and the average plus or minus one standard deviation (i.e. the 68% confidence interval). In the base year, 2013, there was already some uncertainty (a 2% CV) due to the uncertainty of the manufacture parameters (input-output coefficients and manufacturing cost). As the length of the projections increased, the range of projected industrial roundwood consumption increased steadily, ending with a coefficient of variation of 19% in 2065 (Fig. 1a). For the price of industrial roundwood the initial uncertainty was larger in the base year with a CV of 9% in 2014 that increased to 14% in 2065 (Fig. 1b). Nevertheless, for the United States, the industrial roundwood consumption and the price projected with the model with average parameter values were not significantly different from the average consumption and price projected with the replications of the model with randomly drawn parameters.

Table 7
Effect of uncertainty by specific parameter type. Coefficient of variation (%) of predicted industrial roundwood consumption in 2065 for twenty replications with parameters of each type drawn randomly from their assumed distributions, other parameters being held constant at their average value.

	Parameter type				
	Demand	Supply	Forest	Manufacture	Trade
AFRICA	7	5	12	5	6
Egypt	13	21	63	12	9
Nigeria	59	444	310	65	50
South Africa	13	15	30	15	16
N/C AMERICA	18	10	15	10	2
Canada	20	22	52	15	8
Mexico	10	18	21	5	8
United States	21	13	12	16	4
SOUTH AMERICA	6	11	7	9	4
Argentina	12	14	23	7	6
Brazil	5	15	13	11	5
Chile	22	26	38	24	19
ASIA	4	17	10	4	7
China	4	28	11	4	10
India	12	12	41	7	8
Indonesia	8	26	18	4	3
Japan	35	38	36	35	33
Korea, Rep.	14	18	27	27	9
Malaysia	8	17	14	14	12
OCEANIA	15	24	19	21	10
Australia	40	62	58	50	39
New Zealand	18	17	14	22	4
EUROPE	8	7	11	6	6
EU-28	8	7	8	5	3
Austria	28	22	36	33	21
Finland	15	20	37	13	8
France	30	36	43	36	30
Germany	13	12	17	8	10
Italy	32	35	31	20	30
Russian Fed.	17	22	44	29	25
Spain	67	74	70	51	52
Sweden	6	12	41	12	7
United Kingdom	7	10	48	6	5
DEVELOPED	9	4	8	2	3
DEVELOPING	4	15	7	3	5
WORLD	6	8	4	2	1

3.2. Partial effects of uncertainty by parameter type

Table 7 shows the partial effect of uncertainty in each parameter type (demand, supply, forest, manufacture, trade) on the variability of the GFPM projections of industrial roundwood consumption in 2065, measured by the coefficient of variation over twenty replications with parameters of a type selected randomly from their assumed distribution, holding other parameters at their average value.

At world level, the largest variation in 2065 projections was due to uncertainty in the supply and demand elasticities (8% and 6%, respectively), followed the uncertainty in the forest parameters (4%), and the manufacture parameters (2%), while the variation stemming from

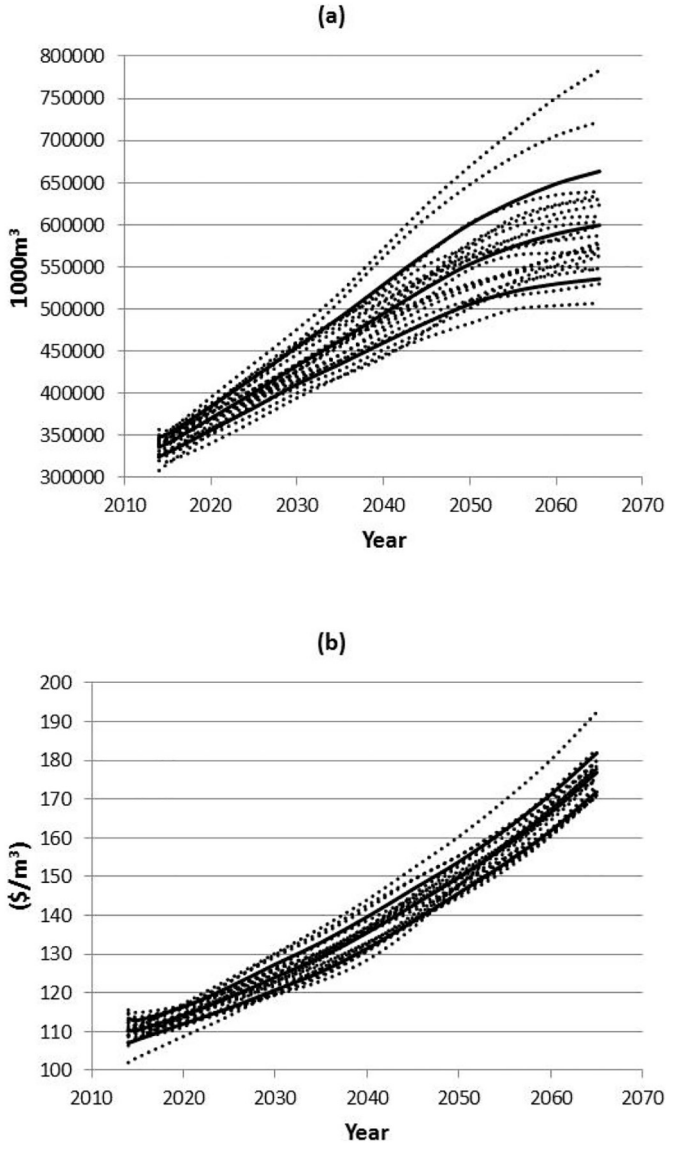

Fig. 2. GFPM projections of industrial roundwood consumption (a) and price (b) in the United States from 2014 to 2065. Dotted lines are twenty replications with initial conditions drawn randomly from their assumed distribution. Solid lines are the average projection and the average plus or minus one standard deviation.

the trade inertia parameters was approximately 1% (Table 7). This order of importance of the parameter type for the variability of the projections tended to persist at region and country level, but with several exceptions. For example, in several European countries, including in Austria, Finland, France, and Russia, the variability of projections induced by the uncertainty of forest parameters exceeded that due to the uncertainty of the other parameters *t*.

3.3. Effects of uncertainty in initial conditions

A result of the replications of projections with different initial conditions is illustrated in Fig. 2. The Figure shows twenty replications and their average, plus or minus one standard deviation of projections of industrial roundwood consumption and price in the United States with base-year data selected randomly from their assumed distribution, and model parameters constant at their average value.

There was less increase over time in the uncertainty of the projections due to different initial conditions compared to that due to parameters uncertainty (Fig. 1). The CV of industrial roundwood consumption went from 3.5% in 2014 to 11% in 2065 (Fig. 2a). The CV of industrial roundwood price stayed approximately constant at 3%, from 2014 to 2065 (Fig. 2b). For both consumption and price, the 2065 projections obtained with the model with average parameter values were not significantly different from the average of the projections with different initial conditions.

At world level, the coefficient of variation of the projections for year 2065 was 2% for industrial roundwood production and consumption, 4% for price, and 7% from imports and exports (Table 8). This larger variability of imports and exports tended to persist at regional and country level, with some exceptions such as the lower CV of imports for France (13%) compared to the CVs of consumption (44%).

Table 8
Effect uncertainty in initial conditions. Coefficient of variation (%) of industrial roundwood production, consumption, import, export, and price in 2065 for twenty replications with base-year data drawn randomly from their assumed distributions, and parameters held at their average value.

	Production	Consumption	Import	Export	Price
AFRICA	6	3	7	16	
Egypt	50	17	10	29	12
Nigeria	309	278	123	285	5
South Africa	13	11	47	19	4
N/C AMERICA	3	7	19	26	
Canada	5	11	21	137	4
Mexico	8	8	109	18	5
United States	4	11	15	32	3
SOUTH AMERICA	3	6	28	131	
Argentina	10	11	155	157	9
Brazil	4	8	54	150	3
Chile	9	9	165	111	6
ASIA	3	4	9	17	
China	4	5	9	18	8
India	6	5	30	40	2
Indonesia	5	5	95	40	5
Japan	5	23	49	21	3
Korea, Rep.	9	9	84	83	6
Malaysia	8	9	94	160	7
OCEANIA	6	19	38	15	
Australia	5	25	52	17	4
New Zealand	10	33	82	73	8
EUROPE	3	5	23	10	
EU-28	3	6	24	31	
Austria	6	28	41	18	4
Finland	9	17	85	20	4
France	7	44	13	70	5
Germany	6	20	114	18	5
Italy	5	27	44	20	3
Russian Fed.	4	10	57	11	3
Spain	8	17	55	134	9
Sweden	7	8	79	21	3
United Kingdom	9	10	70	300	4
DEVELOPED	3	3	19	9	
DEVELOPING	2	3	9	53	
WORLD	2	2	7	7	4

3.4. Effects of parameters uncertainty in impact analysis

Fig. 3 shows twenty replications of the projected percent impact of a rise in temperature of 2.8 °C over a century on the global growing stock and world price of industrial roundwood, measured by the unit value of world exports, with model parameters selected randomly from their assumed distribution and initial conditions held constant. The Figure also shows the - average of the impact, plus or minus one standard deviation. The uncertainty of the projections increased steadily over time. For the world growing stock the projected impact in 2065 was between −0.1% and −1.1% with 68% probability. For price, it was between −1.0% and − 3.0%.

Table 9 shows more geographical detail of the percent impact of

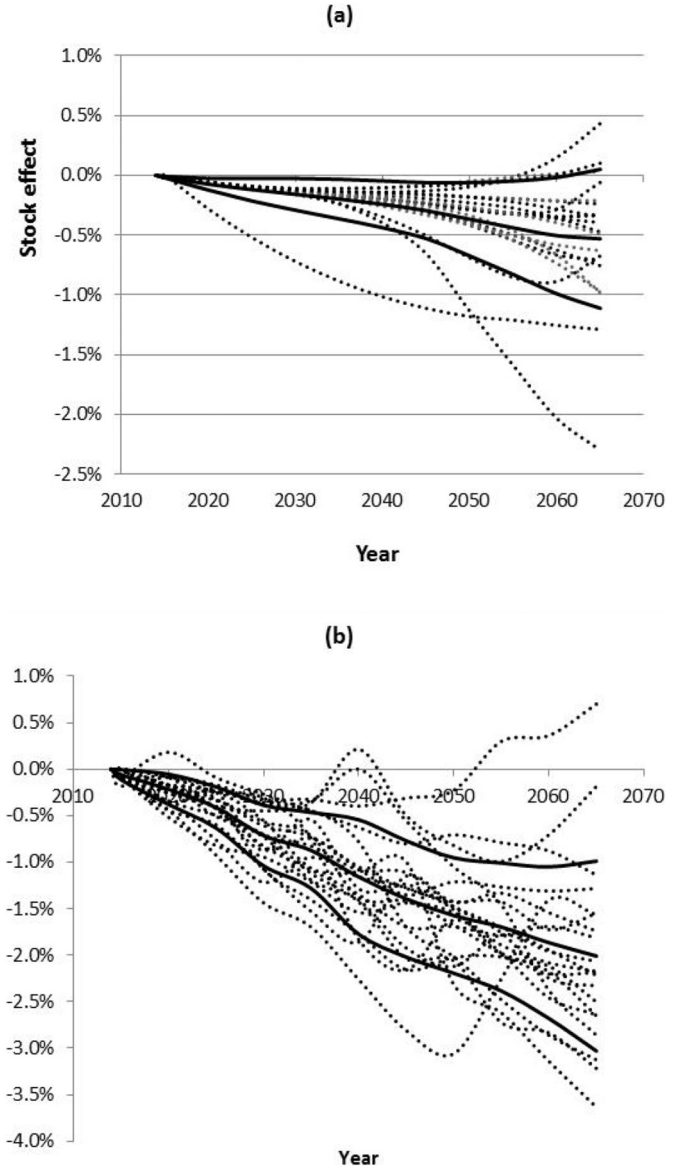

Fig. 3. GFPM projections of the effect of rising temperature on world growing stock (a) and industrial roundwood price (b) from 2013 to 2065. Dotted lines are twenty replications with parameters drawn randomly from their assumed distribution. Solid lines are the average and the average or minus one standard deviation.

temperature change on growing stock and industrial roundwood consumption and price in 2065. While the temperature rise caused the forest stock to be 2.5% to 4% higher in developed countries, it was 2.6% to 3.9% lower in developing countries. Some of the most striking increases in growing stock were in Canada (6.2% to 6.6%) and in Russia (6.8% to 7.1%), while largest negative impacts occurred in Brazil (−3.8% to −4. 7%), Mexico (−2.9% to −6.6%) and India (−2.6% to −3.7%).

The effects of the temperature increase on industrial roundwood consumption (Table 9) tended to mirror the changes in growing stock. Global consumption was 0.3% to 0.8% higher in 2065, but it was 1.2% to 2.6% lower in developing countries while it increased by 2% to 3.3% in developed countries. In Canada, industrial roundwood consumption increased by 5.6% to 11.2% in 2065 due to the rise in temperature, and it increased by 2.7% to 10.9% in Russia. In contrast, Brazilian consumption was 2.1% to 10% lower.

Higher global temperature led to lower prices of industrial roundwood in many developed countries, such as all the European countries in Table 9, although for Germany the 68% confidence interval was −3.5% to 0.4%, and for Spain it was −3.6% to 0.1%, so that the price could very well turn out to be higher. In countries where the temperature change decreased the growing stock significantly at the 68% confidence level, the price effect was also uncertain, ranging for example from −1.6% to 4.3% for Brazil and from −13.7% to 9.9% in India.

Table 9
Effect of parameters uncertainty in impact analysis. Mean and standard deviation (SD) of the percent change in growing stock, industrial roundwood consumption, and industrial roundwood price in 2065 due to rising global temperature, for twenty replications with all parameters drawn randomly from their assumed distribution.

	Forest growing stock (%)		Industrial roundwood consumption (%)		Industrial roundwood price (%)	
	Mean	SD	Mean	SD	Mean	SD
AFRICA	−4.5	0.6	−2.4	1.7		
Egypt	8.7	4.4	0.7	2.2	−1.4	2.0
Nigeria	−74.0		8.1	26.2	6.4	31.6
South Africa	1.6	2.4	1.3	1.8	0.0	5.2
N/C AMERICA	2.3	0.4	2.7	1.2		
Canada	6.4	0.2	8.4	2.8	−2.5	0.8
Mexico	−4.7	1.9	−7.9	4.9	1.0	3.9
United States	1.2	0.3	0.6	2.5	−1.7	0.8
SOUTH AMERICA	−3.7	0.6	−4.5	2.9		
Argentina	1.1	0.5	−0.1	1.0	−2.0	0.9
Brazil	−4.2	0.4	−6.0	4.0	1.3	3.0
Chile	2.0	1.5	0.8	1.1	−2.3	1.2
ASIA	−0.7	0.9	−1.0	0.6		
China	2.7	3.8	1.1	3.3	−1.8	0.9
India	−3.2	0.5	−2.8	6.2	−1.9	11.8
Indonesia	−5.9	5.9	−5.6	2.5	1.6	4.9
Japan	1.8	0.6	−0.5	2.3	−2.6	1.7
Korea, Rep.	0.8	0.2	0.1	0.5	−1.5	0.6
Malaysia	−3.1	0.6	−5.3	3.0	0.2	2.5
OCEANIA	−2.7	0.4	1.0	2.4		
Australia	−3.7	0.4	0.3	4.1	−1.8	1.0
New Zealand	1.6	1.0	1.4	2.8	−2.2	1.0
EUROPE	4.0	1.1	2.7	1.0		
EU-28	1.4	0.5	1.6	1.2		
Austria	1.4	0.7	1.1	3.7	−1.7	2.0
Finland	2.7	1.3	6.1	2.6	−1.9	1.2
France	1.3	0.5	−0.8	3.1	−2.1	1.3
Germany	1.1	0.4	0.3	1.9	−1.6	1.9
Italy	1.1	0.4	−1.0	3.8	−1.8	1.0
Russian Fed.	7.0	0.2	6.8	4.1	−3.5	1.9
Spain	1.9	1.1	0.0	5.6	−1.8	1.9
Sweden	3.2	1.8	5.7	3.9	−2.4	1.7
United Kingdom	3.4	1.9	1.0	2.4	−2.9	2.1
DEVELOPED	3.2	0.8	2.6	0.6		
DEVELOPING	−3.2	0.7	−1.9	0.7		
WORLD	−0.6	0.5	0.6	0.3	−2.1	0.9

4. Discussion and conclusion

This study explored the consequences for long-term projections and impact analysis of the uncertainty in model parameters and basic data. Using the Global Forest Products Model, multiple replications of projections were carried out with parameters or base-year data sampled randomly from their assumed distribution. The results showed that parameter uncertainty led to steadily increasing variability of projections with time, and more rapidly than the uncertainty stemming from initial conditions. Among the parameter uncertainties, those in the demand and supply elasticities tended to dominate the effect of uncertainties in parameters of forest change, manufacturing activities, and trade inertia. In an application to climate change analysis it was found that, due only to the uncertainty of the GFPM parameters, an assumed

rise in global temperature of 2.8 °C over a century caused the forest stock to be 2.4% to 4.0% higher in developed countries, and 2.5% to 3.9% lower in developing countries, with 68% probability, a conservative estimate of the true uncertainty given all the other assumptions involved in such a projection.

Such wide confidence intervals have implications for forest sector outlooks like those of the Food and Agriculture Organization of the United Nations (FAO) and the US Forest Service Resource Planning Act (RPA) assessment. These studies, which produce long-term forest sector projections that influence policy, are based on models that rely on historical data and parameters with unavoidable inherent uncertainty. The consequences of this uncertainty for projections and impact analysis should be fully recognized. At the same time, the uncertainty can be decreased through improved data collection, econometric research, and scenario building methods.

The finding that while uncertainty in the initial conditions was carried forward in projections, uncertainty in parameter estimates caused large divergence in projections suggests that a potentially high payoff for future research is to concentrate on parameter estimation. Among all parameters, the most promising for improvement are the elasticities of demand for end products and the elasticities of wood supply. In this respect, new results concerning for example demand elasticities (Johnston, 2016) could be used to advantage.

This study has been concerned about the influence of uncertainty in initial conditions and model parameters on the projection of endogenous variables of the forest sector, such as production, price, and trade, the core area of forest economics research. However, projections of forest sector models must also rely on projections or assumptions of exogenous variables such as population and gross domestic product projected by demographers and macroeconomists. In many situations, uncertainty of these exogenous projections may well be the dominant source of uncertainty for the future of the forest sector. For example, Kallio (2010) finds that in a model of Finland, world prices of forest products (assumed exogenous) are the main source of uncertainty in projections for the forest sector. In the present paper, the large uncertainty concerning the effects of climate change, derived from the quantified work of Way and Oren (2010) on the effect of temperature on the growth of trees, is still only a part of the large uncertainty surrounding the potential effects of climate change.

In the near term, forest sector modeling may well continue to deal with macroeconomic/environment uncertainty with alternative scenarios. This approach has been used in several studies, such as Nepal et al. (2012) who project U.S. forest sector carbon sequestration to 2060 with the USFPM/GFPM model based on four different scenarios concerning global economic and demographic growth. One promising development in this respect has been to harmonize assumptions regarding plausible futures. The Shared Socioeconomic Pathways (SSPs) established in connection with the IPCC (O'Neill et al., 2015, Samir and Lutz, 2017) represent such a procedure for establishing a coherent narrative regarding assumptions on exogenous variables including income, demographics, technology, and policy.

Nevertheless, future research should strive to attach specific probabilities to these exogenous scenarios, analog to the probable range of outcomes found for the endogenous variables in this paper. This combined uncertainty of variables within and outside the forest sector is likely to lead to very uncertain projections, and their confidence intervals for long periods may become so wide that they are of limited use with existing decision making methods. Thus, besides improving current models and data, how to optimize policy while recognizing the wide uncertainty of model projections should be the ultimate goal of future research.

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